Engineering

Mechanical Engineering fields

Okayama University *Year* 1995

Fuzzy fault diagnostic system based on fault tree analysis

Zong Xiao Yang
Okayama University

Kazuhiko Suzuki
Okayama University

Yukiyasu Shimada
Okayama University

Hayatoshi Sayama
Okayama University

Fuzzy Fault Diagnostic System based on Fault Tree Analysis

Zong-Xiao YANG *, Kazuhiko SUZUKI, Yukiyasu SHIMADA *and* Hayatoshi SAYAMA

Faculty of Engineering
Okayama University, Tsushima-naka, Okayama 700, Japan

* *Graduate School of Natural Science and Technology*
Okayama University, Tsushima-naka, Okayama 700, Japan

Key words : Fuzzy expert system, Fault tree analysis, Fuzzy sets, Fault diagnosis

Abstract- **A method is presented for process fault diagnosis using information from fault tree analysis and uncertainty / imprecision of data. Fault tree analysis, which has been used as a method of system reliability / safety analysis, provides a procedure for identifying failures within a process. A fuzzy fault diagnostic system is constructed which uses the fuzzy fault tree analysis to represent a knowledge of the causal relationships in process operation and control system. The proposed method is applied successfully to a nitric acid cooler process plant.**

1 Introduction

Fault tree analysis is useful for system reliability analysis and risk quantification since which illustrates the failure logic of a system, and shows combinations and sequences of failure which can lead to a failure condition under consideration (the top event). The fault diagnostic expert system is developed which uses fault tree analysis for representation and acquisition of knowledge from the process operation and control system[1-4]. For many systems, estimation of qualitative / quantitative information from fault tree analysis is difficult due to uncertainty and imprecision of information about process malfunction.

In this paper, we use fuzzy set logic to account for imprecision and uncertainty in information and data while employing fault tree analysis. Qualitative information of fault tree analysis, i.e. minimal cut sets from a fault tree, is transformed into the knowledge base in the form of production rules. Quantitative information which obtained by fuzzy fault tree analysis is used to determine the certainty factors and stored in the knowledge base. The fuzzy fault diagnostic system can identify component failures and process disturbances which can lead to system malfunctions by matching the process uncertainty data from the plant with the pattern of IF statements stored in the computers. From the uncertainty detected data and knowledge, the system also evaluates certainty factors of component failures and process disturbances for sequence checking in diagnosis. A nitric acid cooler process plant is used to demonstrate the effectiveness of the proposed method.

2 Fault tree for nitric acid cooler process

A nitric acid cooler process with temperature feedback and pump shutdown feedforward loops is illustrated in Fig.1[5]. The function of this process is to cool a hot nitric acid stream before reacting it with Benzene to form Nitrobenzene. Numbers 1-14 in circles in the plant of Fig.1 show nodes which are the connecting points of components. The following notation is used to describe deviations in process variables at nodes: T, F, P(ΔP) denote deviations in temperature, flow rate and pressure respectively. Hence, to represent an increase in the flow rate at node7, write F7 high. The undesired event for the system is a high temperature in the nitric acid reactor feed since this could cause a reactor runaway. In this study, T4 high (high temperature in the effluent stream of nitric acid) is selected as the top event. Fig.2 shows the fault tree of the process for the top event (T4 high).

Process variables in the fault tree of Fig.2 can be divided into two groups: A type and B type. The A type such as too high, high, normal, low and too low is used to describe disturbances in the process. Too high, too low denote large deviations in the high, low direction respectively which can not be corrected by a control loop, and high, low denote deviations which can be corrected. The B type such as more, less is used to discribe deviations which occured in a control loop and protective system. More, less denote no signal to cancel the effect of deviations in the process variables, and normal denotes a standard state.

3 Knowledge representation and acquisition

Fault tree analysis is used for the representation and acquisition of knowledge from the process operation and control system. The fault propagation in process is modeled by causal relationships from the qualitative information, i.e. a fault tree and it's minimal cut sets. The method can determine the minimum number of sensors and the monitoring points to detect basic events in the process[3]. Table1 shows twenty-two minimal cut sets of the fault tree, and the allocation of twelve sensors in circles is illustrated in Fig.1, such as flow sensor F2 for F2 more and F2 high and F2 too high, temperature sensor T2 for T2 high and T2 too high, pressure sensor P10 for P10 less and P10

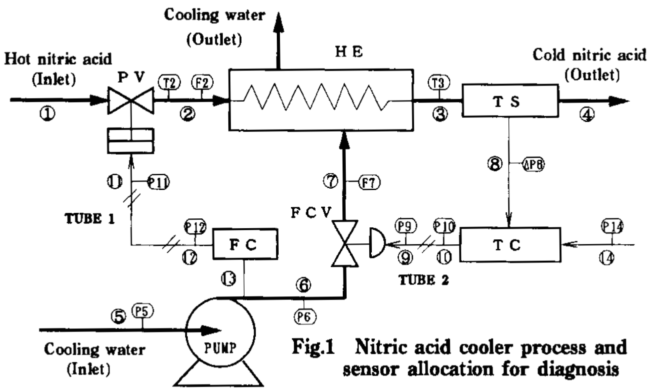

Fig.1 Nitric acid cooler process and sensor allocation for diagnosis

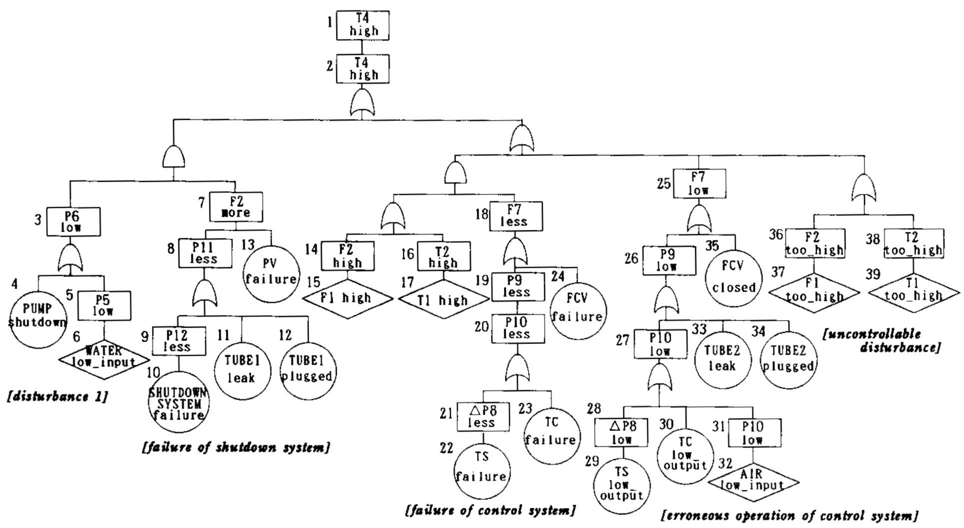

Fig.2 Fault tree of nitric acid cooler process for T4 high

low, and so on.

Based on the minimal cut sets for the nitric acid cooler process, the qualitative information can be transformed into production rules. For example, the cutset(5,[6,10]) shows that a disturbance and a failure of shutdown system could cause T4 high. The disturbance (Water

Table 1 Minimal cut sets of fault tree

Minimal cut set	Classifications
cutset (1,[4,10]).	1) Disturbance and Shutdown system failure
cutset (2,[4,11]).	
cutset (3,[4,12]).	
cutset (4,[4,13]).	
cutset (5,[6,10]).	
cutset (6,[6,11]).	
cutset (7,[6,12]).	
cutset (8,[6,13]).	
cutset (9,[15,22]).	2) Disturbance and Control system failure
cutset (10,[15,23]).	
cutset (11,[15,24]).	
cutset (12,[17,22]).	
cutset (13,[17,23]).	
cutset (14,[17,24]).	
cutset (15,[29]).	3) Erroneous operation of control system
cutset (16,[30]).	
cutset (17,[32]).	
cutset (18,[33]).	
cutset (19,[34]).	
cutset (20,[35]).	
cutset (21,[37]).	4) Uncontrollable disturbance
cutset (22,[39]).	

Table 2 Failure rates of basic events and subjective estimation factors

Classification	Event numbers	Basic event	Failure rate	K
Component failure	10	Shutdown system failure	$6.580*10^{-6}$	1/3
	11,33	Tube leak	$1.786*10^{-6}$	
	12,34	Tube plugged	$5.323*10^{-6}$	
	13	PV failure	$7.750*10^{-6}$	
	22	TS failure	$10.540*10^{-6}$	
	23	TC failure	$21.010*10^{-6}$	
	24	FCV failure	$7.750*10^{-6}$	
Erroneous operation	29	TS low_output	$2.477*10^{-6}$	7/24
	30	TC low_output	$3.117*10^{-6}$	
	32	Air low_input	$0.992*10^{-6}$	
	35	FCV closed	$1.790*10^{-6}$	
Disturbance	4	Pump shutdown	$1.917*10^{-6}$	1/4
	6	Water low_input	$0.992*10^{-6}$	
	15	F1 high	$4.948*10^{-6}$	
	17	T1 high	$1.554*10^{-6}$	
	37	F1 too_high	$5.953*10^{-6}$	
	39	T1 too_high	$3.196*10^{-6}$	

```
/*     ***** RULE FORMULATIONS ******** #P8 = ΔP8 *****      */
Rule00:
  IF T3 is normal, THEN The system is running on normally.
Rule01 (CF_rule is 0.155):
  IF T3 is high & F2 is more & P5 is not_low & P6 is low & P11 is less & P12 is less, THEN Pump is shutdown & Shudown_system is failure.
Rule02 (CF_rule is 0.268):
  IF T3 is high & F2 is more & P5 is not_low & P6 is low & P11 is less & P12 is not_less, THEN Pump is shutdown & (Tube1 is leak or plugged).
Rule03 (CF_rule is 0.159):
  IF T3 is high & F2 is more & P5 is not_low & P6 is low & P11 is not_less, THEN Pump is shutdown & PV is failure.
Rule04 (CF_rule is 0.152):
  IF T3 is high & F2 is more & P5 is low & P6 is low & P11 is less & P12 is less, THEN Water is low_input & Shudown_system is failure.
Rule05 (CF_rule is 0.246):
  IF T3 is high & F2 is more & P5 is low & P6 is low & P11 is less & P12 is not_less, THEN Water is low_input & (Tube1 is leak or plugged).
Rule06 (CF_rule is 0.155):
  IF T3 is high & F2 is more & P5 is low & P6 is low & P11 is not_less, THEN Water is low_input & PV is failure.
Rule07 (CF_rule is 0.174):
  IF T3 is high & F2 is high & F7 is less & #P8 is less & P10 is less, THEN F1 is high & TS is failure.
Rule08 (CF_rule is 0.198):
  IF T3 is high & F2 is high & F7 is less & #P8 is not_less & P10 is less, THEN F1 is high & TC is failure.
Rule09 (CF_rule is 0.163):
  IF T3 is high & F2 is high & F7 is less & P10 is not_less, THEN F1 is high & FCV is failure.
Rule10 (CF_rule is 0.167):
  IF T3 is high & T2 is high & F7 is less & #P8 is less & P10 is less, THEN T1 is high & TS is failure.
Rule11 (CF_rule is 0.186):
  IF T3 is high & T2 is high & F7 is less & #P8 is not_less & P10 is less, THEN T1 is high & TC is failure.
Rule12 (CF_rule is 0.158):
  IF T3 is high & T2 is high & F7 is less & P10 is not_less, THEN T1 is high & FCV is failure.
Rule13 (CF_rule is 0.186):
  IF T3 is high & F7 is low & #P8 is low & P9 is low & P10 is low, THEN TS is low_output.
Rule14 (CF_rule is 0.194):
  IF T3 is high & F7 is low & #P8 is not_low & P9 is low & P10 is low & P14 is not_low, THEN TC is low_output.
Rule15 (CF_rule is 0.157):
  IF T3 is high & F7 is low & P9 is low & P10 is low & P14 is low, THEN AIR is low_input.
Rule16 (CF_rule is 0.172):
  IF T3 is high & F7 is low & P9 is low & P10 is not_low, THEN Tube2 is leak or Tube2 is plugged.
Rule17 (CF_rule is 0.216):
  IF T3 is high & F7 is low & P9 is not_low, THEN FCV is closed.
Rule18 (CF_rule is 0.310):
  IF T3 is high & F2 is too_high, THEN F1 is too_high.
Rule19 (CF_rule is 0.278):
  IF T3 is high & T2 is too_high, THEN T1 is too_high.
```

Fig.3 Knowledge base about T4 high for diagnosis low_input) will occur if cooling water pressure P6 and P5 are observed to be low both. And the shutdown systen failure will be find by that pressure P11, P12 are known to be less and flow rate F2 to be more. Also the top event (T4 high) will be found if temperature T3 is known to be high. This one can be transformed into a production rule as shown below.

IF T3 is high & F2 is more & P5 is low & P6 is low & P11 is less & P12 is less
THEN Water is low_input & Shutdown_system is failure

The production rules which are obtained in the same way are shown in Fig.3. Besides, we can deduce a component failure, such as Event13 (PV failure) in Fig.2 will occur, from the exclusive information of Event8 (P11 is less), and write this information in IF statement of rules as P11 is not_less.

4 Fuzziness in rules

An imprecision of component failure or process disturbance can be described by using the failure rate and the subjective estimation factor. We call it a fuzzy failure measure, and give it by

$$f(\lambda, K)=\begin{cases} \dfrac{1}{1+(K*\log(1/\lambda))^3}, & 0<\lambda\leq 1 \\ 0, & \lambda=0 \end{cases} \tag{1}$$

where, λ is a failure rate of component shown in Table2 for the nitric acid cooler process[7], and K is a parameter which called a subjective estimation factor. The more smaller of K, the more stronger of evaluation for failure rate. The value of K for the process is also shown in Table2.

When THEN statement in production rules are composed of two basic events with logical multiply or logical sum, we will use the fuzzy failure measure f_1, f_2 to describe the fuzziness of multiply with a t-norm of Dombi's type[8]:

$$T(f_1, f_2)=\begin{cases} \dfrac{1}{1+\left\{\left(\dfrac{1-f_1}{f_1}\right)^3+\left(\dfrac{1-f_2}{f_2}\right)^3\right\}^{1/3}}, & 0<f_1,\ f_2\leq 1 \\ 0, & f_1=0,\ or\ f_2=0 \end{cases} \tag{2}$$

Given a t-norm T one can consider the dual of T(called a t-conorm) defined by

$$S(f_1, f_2)=1-T(1-f_1, 1-f_2)$$

$$=\begin{cases} \dfrac{\left\{\left(\dfrac{f_1}{1-f_1}\right)^3+\left(\dfrac{f_2}{1-f_2}\right)^3\right\}^{1/3}}{1+\left\{\left(\dfrac{f_1}{1-f_1}\right)^3+\left(\dfrac{f_2}{1-f_2}\right)^3\right\}^{1/3}}, & 0\leq f_1,\ f_2<1 \\ 1, & f_1=1,\ or\ f_2=1 \end{cases} \tag{3}$$

therefore, the S function will be used to describe the fuzzness of logical sum for THEN statement.

We use certainty factors of production rule, in writting CF_rule, to deal with the uncertainty of the information in the knowledge base. A CF_rule means a certainty factor in THEN statement of a rule under it's IF statement occurred exactly, and defined by Equation(4).

$$CF\_rule(x)=\begin{cases} f, & x=E \\ T(f_1, f_2), & x=E1\ \&\ E2 \\ S(f_1, f_2), & x=E1\ or\ E2 \\ T(f_1, S(f_2, f_3)), & x=E1\ \&\ (E2\ or\ E3) \end{cases} \tag{4}$$

where, E is the members of THEN statement in a rule, such as $E1$=Pump is shutdown, $E2$=Tube1 is leaking, $E3$=Tube1 is plugged for Rule02 in Fig.3.

From above equations and data in Table2, a result of CF_rule is obtained for the nitric acid cooler process plant, and stored in knowledge base as shown Fig.3.

5 Fuzziness in process variables

We can consider a process variable in fault tree as a fuzzy set. Uncertainty about process variables, which detected from sensor readings, is dealt with through membership functions, and transformed to certainty factors of sensor readings. The shape and relation for these fuzzy sets with process variables appear as Fig.4[9].

A negation of process variable, such as P5 is not_low, is represented by a λ-fuzzy set complement $\mu_{not\_A}(x)$, and give the set by

$$\mu_{not\_A}(x)=\frac{1-\mu_A(x)}{1+\lambda*\mu_A(x)} \tag{5}$$

Table3 shows an example of sensor readings at twelve monitoring points. We can calculate certainty factors of process variables by the membership functions and sensor readings, and result in Table3. From the fuzziness of process variables, certainty factors about IF statements in knowledge base will be determined.

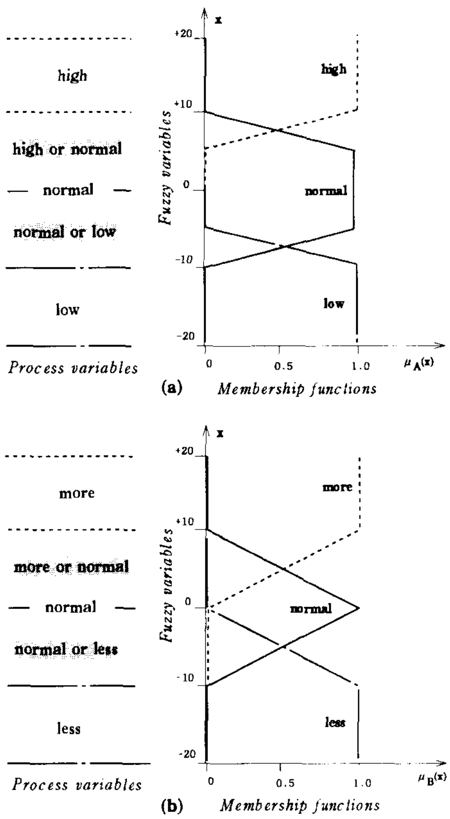

Fig.4 Membership functions
((a) for A type and (b) for B type)

Table 3 Example of sensor readings and uncertainty

No.	Sensor readings	Certainty factor					
		A type			B type		
		HIGH	NORMAL	LOW	MORE	NORMAL	LESS
1	F2=9.0	0.80	0.20		0.90	0.10	
2	T2=5.0		1.00				
3	T3=10.5	1.00					
4	P5=-6.5		0.70	0.30			
5	P6=-9.5		0.10	0.90			
6	F7=0.0		1.00			1.00	
7	ΔP8=0.0		1.00			1.00	
8	P9=0.0		1.00				
9	P10=0.0		1.00			1.00	
10	P11=-8.5		0.30	0.70		0.15	0.85
11	P12=-2.5		1.00			0.75	0.25
12	P14=5.0		1.00				

6 *Fault diagnosis*

The fuzzy expert system attempts to identify the component failures and process disturbances which can lead to system malfunction by searching through the IF statements of rules in Fig.3 corresponding to process data from the plant such as sensor readings in Table3. The pattern recognition in inference engine is completed by means of which a pruduction rule will fire through certainty factor in IF statement of the rule. Assume a IF statement having N members with $CF\_pv(1)$, $CF\_pv(2)$, $\cdots$, $CF\_pv(N)$, the certainty factor in the IF statement can be presented in the form:

$$CF\_if=CF\_pv(1)\wedge CF\_pv(2)\wedge\cdots\wedge CF\_pv(N) \quad (6)$$

For example, using the values of CF_pv for sensor readings in Table3, six rules (Rule01–Rule06) would fire and infer that T4 high could result from the disturbance and the pump shutdown feadforward loop failure. In turns, the expert *system identify the positive causes in* THEN statements which are composed of component failures and disturbances, and *reasoning results are shown in* Table4.

Table 4 Reasoning results for the example

Rule No.	Positive Causes	CF_if	CF_rule	CF_then	Check list No.
01	Pump shutdown & Shutdown_system failure	0.25	0.155	0.0388	3
02	Pump shutdown & Tubel leak or plugged	0.65	0.268	0.1742	1
03	Pump shutdown & PV failure	0.124	0.159	0.0197	5
04	Water low_input & Shutdown_system failure	0.25	0.152	0.0380	4
05	Water low_input & Tubel leak or plugged	0.30	0.246	0.0738	2
06	Water low_input & PV failure	0.124	0.155	0.0192	6

Finally, sequence checking in diagnosis for complex positive causes is carry out in the expert *system through evaluating certainty factors of* THEN statements for fired rules by a multiplication.

$$CF\_then=CF\_if * CF\_rule \quad (7)$$

A checking sequence as same example for

nitric acid cooler process is also appeared on Table4. As a result of diagnosis using fault tree analysis and certainty factors, the system can successfully diagnose any single or multiple faults in the plant.

7 Conclusion

In this paper, a fuzzy fault diagnostic system is developed which uses fuzzy set logic to accout for uncertainty in information and data while employing fault tree analysis. Qualitative information, minimal cut sets, of fault tree analysis is used for the representation and acquisition of knowledge, and transformed into production rules. Fuzziness in rules is determined based on a fuzzy failure measure, a t-norm, a t-conorm, and stored in knowledge base as certainty factors. As demonstrated, the positive causes of system failure can be identified effectively by reasoning through process uncertainty data from the plant and production rules. A checking sequence for complex positive causes in diagnosis is evaluated from certainty factors of THEN statements for fired rules.

References

1 S. H. Rich, V. Venkatasubramanian: Model-based Reasoning in Diagnostic Expert Systems for Chemical Process Plants; Comput. Chem. Eng., Vol.11, No.2, pp111-122(1987)

2 N. H. Ulerich, G. J. Powers: On-line Hazard Aversion and Fault Diagnosis in Chemical Processes: The Digraph+Fault-Tree Method; IEEE Trans. on Reliability, Vol.R-37, No.2, pp171-177(1988)

3 H. Sayama, et al.: Study on Fault Diagnostic Method for Process using Fault Trees.
1st Report, Sensor Allocation for Fault Diagnosis; Journal of the Society of Plant Engineers Japan, Vol.1, No.2, pp13-20(1990).
2nd Report, Development of Fault Diagnostic Expert System; Journal of the Society of Plant Engineers Japan, Vol.2, No.1, pp11-20(1990).

4 K. Suzuki, Y. Shimada, H. Sayama: Development of Fault Diagnostic Expert System using Fault Trees; Journal of Japan Society for Safety Engineering, Vol.31, No.2, pp100-109(1992)

5 S. A. Lapp, G. J. Powers: Computer-aided Synthesis of Fault-trees; IEEE Trans. on Reliability, Vol.R-26, No.1, pp2-13(1977)

6 L. A. Zadeh: The Role of Fuzzy Logic in the Management of Uncertainty in Expert Systems; Fuzzy Sets and Systems, Vol.11, pp199-227(1983)

7 IEEE Inc.: IEEE Guide to the Collection and Presentation of Electrical, Electronic, and Sensing Component Reliability Data for Nuclear Power Generating Stations; The Institute of Electrical and Electronic Engineers, Inc.(1977)

8 M. Mizumoto: Pictorial Representations of Fuzzy Connectives, Part I: Cases of t-norms, t-conorms and Averaging Operators; Fuzzy Sets and Systems, Vol.31, pp217-242 (1989)

9 E. Cox: The Fuzzy Systems Handbook: A Practitioner's Guide to building, using, and maintaining Fuzzy Systems; Academic Press, Inc.(1994)